# Evaluation of Remote Sensing Approaches to Monitor Crop Conditions under Specific Input Levels and Cropping Diversity

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**Key Words**: crops, input and diversity levels, leaf area index (LAI), hyperspectral remote sensing, vegetation indices (VIs)

**Abstract**

This study was conducted as part of the Alternative Cropping Systems (ACS) study at Scott, Saskatchewan. The 18 year study was initiated in 1995 to evaluate the sustainability of nine arable crop production systems. The nine cropping systems, derived from combinations of three input levels (organic, reduced, and high) and three cropping diversity levels (low, diversified annual grains, and diversified annual perennials), were designed to monitor and assess alternative input use and cropping strategies for arable crop production on the Canadian Prairies. Field data including leaf area index (LAI) and spectral reflectance were collected three times during the growing season of 2003: early growing season (June), mid growing season (July) and late growing season (August). LAI was measured with an LAI-2000 plant canopy analyzer. The spectral measurements were made with a handheld ADS spectroradiometer, which covers wavelengths from 350 nm to 2500 nm with 2151 bands. Results showed that remote sensing can be used to indicate different crop conditions. The spectral and LAI differences among input levels were significant at early to mid growing seasons. Mid July was the best season and the red over near infrared spectral ratio as well as the normalized difference vegetation index based on these two bands were the best vegetation indices to use for crop vigor monitoring.

**Introduction**

Remote sensing technologies have been widely applied to agriculture, such as in soil survey (including land cover and land use), agricultural resource investigations and meteorological disaster inspections, especially for monitoring crop vigor and predicting crop yields (Gitelson *et al.* 1996). Remote sensing can be used to monitor crop health, growth status and changes of crops in large areas. Growth and development parameters, such as leaf area, leaf color and leaf moisture content result in variation in spectral reflectance. The changes in the spectral reflectance and various vegetative indices can be monitored during the growing season of the crop to access changes in crop vigor. .

Most of the research reported in the literature has been developed using conventional remote sensing data from a few crops. However, it has been difficult to response to special spectral features and difference among vegetation because of fewer wavelength and lower spectral resolution in conventional broad band remote sensing data, such as Landsat Thematic Mapper (TM), and also it was easily influenced by other factors such as vegetative cover, leaf color and soil color that reduce the accuracy of monitoring. Hyperspectral remote sensing, with higher spectral resolution and imaging spectrum data of numerous wavelengths, is able to solve some of the problems that occur with conventional remote sensing data and also to decrease the impact of other factors which will increase monitoring preciseness (Malthus and Madeira 1993).

Studies on hyperspectral remote sensing generally focus on the potential of spectral data for estimating biochemical parameters (Card et al. 1988), chlorophyll content of leaves (Chappelle *et al.* 1992, Daughtry *et al*. 2000) and biomass of crops (Wang *et al*. 1993). Few investigations have dealt with the relationship between the Leaf Area Index (LAI) of crops and the hyperspectral reflecting features of crop leaves. The objectives of this study were 1) to identify suitable seasons, hyperspectral wavelength regions and vegetative indices fitting for monitoring Leaf Area Index (LAI), 2) to evaluate the methods of monitoring crop vigor using hypersptctral remote sensing data, and 3) to quantify LAI of wheat using first derivative from hyperspectral bands.

## Material and Methods

This study was conducted at Agriculture and Agri-Food Canada's Alternative Cropping Systems (ACS) experiment site located at Scott, SK ($52^0$22'19"N, $108^0$52'33"W). The experiment is a four replicate split plot experiment with main plot treatments consisting of three input levels (Organic, Reduced and High) and sub-plots comprised of three cropping diversity levels (Low, Diverse Annual Grains and Diverse Annual Perennial) each on a six year rotation cycle (Figure 1) (Ulrich *et al*. 2001).

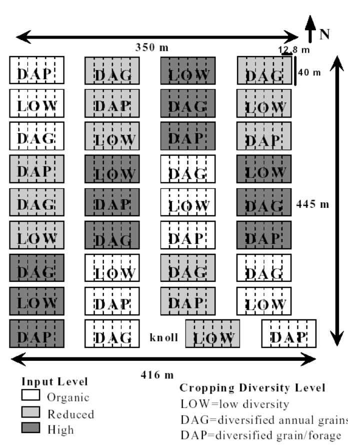


Figure 1. Scott AAFC ACS experiment field layout (Adapted from Ulrich *et al*. 2001).

In 2003, LAI and field level remotely sensed data were collected in the first two replicates at three times during the growing season: early growing season (June 13), mid growing season (July 18) and late growing season (August 11). LAI was collected with a Li-Cor LAI-2000 Plant Canopy Analyzer and remotely sensed data were collected using an ASD portable Spectroradiometer with spectral range of 350-2500 nm. Digital pictures were taken for each plot on each date. For each plot, spectral data were the average of five measurements. LAI was the average of three measurements each with one above canopy reading and five below canopy readings. Spectral readings were collected within two hours of solar soon on very clear days (10:30am-1:30pm). Calibration was made every 10-15 minutes to a white reflectance panel (LabSphere Spectralon) board. LAI-2000 was shaded when observations were being taken to reduce the effect of glazing from direct sunshine.

Based on sample requirements for statistics, only mean spectral response curves of wheat, barley and canola were plotted against wavelength to determine the best season for remote sensing application. Investigation of input levels was studied on wheat only. Pearson's Correlation analysis was conducted for LAI with each single band, first derivative, and different vegetation indices (Table 1). Stepwise regression analysis was applied with spectral indices that showed a significant relationship with LAI. The developed regression model was tested by fitting field measurements into the equation to test the accuracy. Spectral data were also simulated to Landsat TM red and near infrared bands to calculate the normalized difference vegetation index (NDVI) to test the difference of significance among different treatments using analysis of variation (ANOVA) test. Spectral data preprocessing was based on FieldSpec v2.1 software that was included with the equipment and SPSS v11.5 was used for statistical analysis.

## Results

### *Spectral responses of wheat, barley and canola over the growing season.*

Figure 2 shows the spectral characteristics of spring wheat, barley and canola over the growing season. All three crop types showed typical vegetation spectral curves in July with higher near infrared reflectance and lower red reflectance because of chlorophyll absorption and the spectral difference among them is obvious. In June, crops were emerging and bare ground was dominating the spectral component as all spectral curves were close to each other and there was no significant red absorption region. July could be the best season for crop study using remote sensing as plants reached to maximum photosynthesis activity as indicated by strong red and water absorptions in red and middle infrared wavelength regions and plant cell structural reflectance in near infrared region. In August, the measurements were made prior to harvest. The linear line from visible to near infrared wavelength region indicated that wheat and barley had senesced. Canola showed moderate photosynthesis activity during the late growing season. However, for wheat, the optimal growing stage is prior to barley and canola spectrally as the spectral curves showed photosynthesis trend in June and the chlorophyll absorption is reduced in July and the line is more straight in August.

### *Relationship between LAI and growth vigor for wheat*

Spectrally and biophysically, input levels significantly influenced the vigor of the spring wheat crop. The three measurements during the growing season coincided with the spring wheat growth stages of elongation, flag leaf and milk stage, respectively. The wheat LAI curve was parabolic during the growing season (Figure 3), being low at early stage and late stage but being high at flag leaf stage at which wheat was in vigorous growth. Under the three input levels, LAI values were different significantly (P=0.016, 0.028 and 0.010 respectively), in which LAI was greatest for high and least for organic treatments. The results show that wheat growth conditions under high treatment were the best and photosynthetic area was the largest while growth conditions of the wheat under organic treatment were the worst and plant photosynthesis was the lowest. Spectral response curves of wheat under three treatments were plotted in Figure 4 and the ANOVA test was applied for their NDVI values. Results showed that the spectral differences were only significant at early and mid growing seasons (P=0.000, 0.007 and 0.341 respectively). Digital pictures showed the visual differences of wheat under three inputs levels over the growing season (Figure 4). The results indicated that crop vigor can be monitored, and analysis of LAI of wheat using remote sensing data can be used to monitor growth and vigor of the crop.

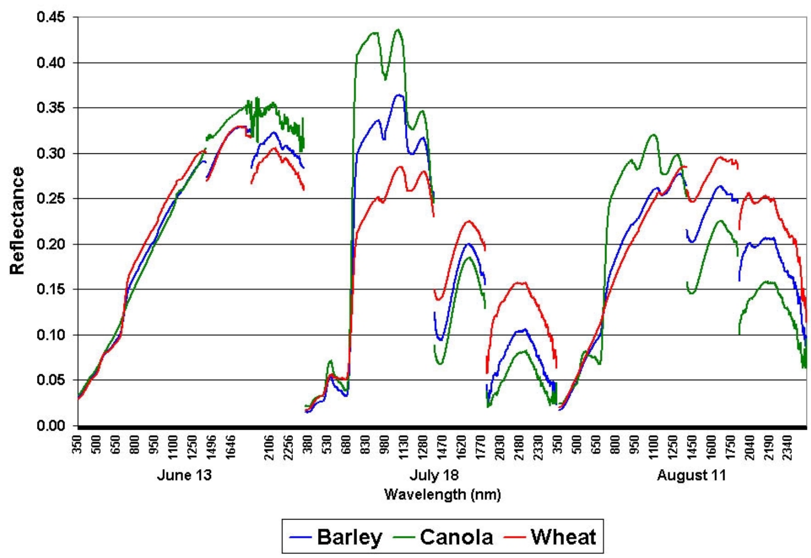


Figure 2. Spectral response curves of wheat, barley and canola in the experiment field during the growing season of 2003. Noisy regions were deleted at around 1300, 1900 and 2500nm.

***The relationship between wheat LAI and hyperspectral reflectance***

*The valid time of monitoring growth vigor of wheat*

A correlation analysis between wheat LAI and hyperspectral reflectance was carried out (Figure 6). Correlation coefficients at different sampling times indicated that values for July $18^{th}$ were the highest and were the lowest for August $11^{th}$. The reasons why values in August were poor are that wheat had matured and was senescing (leaves have wilted, turned yellow and lost water), and the impact on the spectrum is larger than the impact on the LAI.

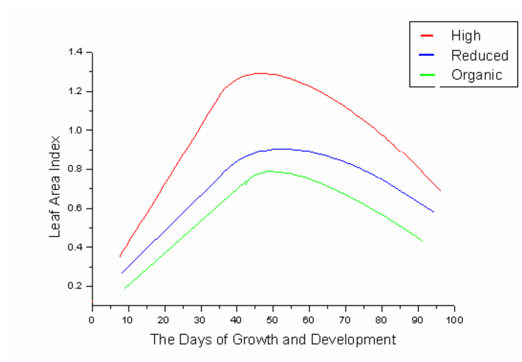


Figure 3. LAI of wheat under three input levels over the growing season. The figure was smoothed by continuously measured LAI data in the growing season of 1997 at Scott.

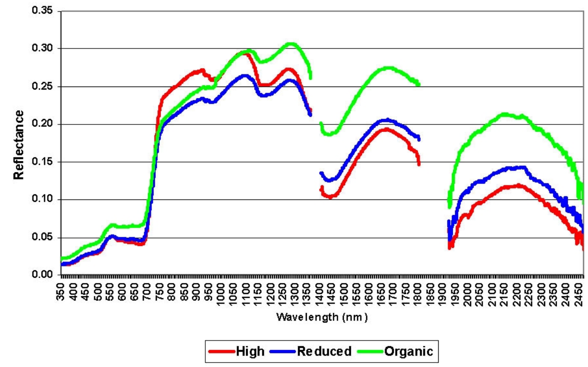


Figure 4. Spectral response curves of wheat under three input levels in July.

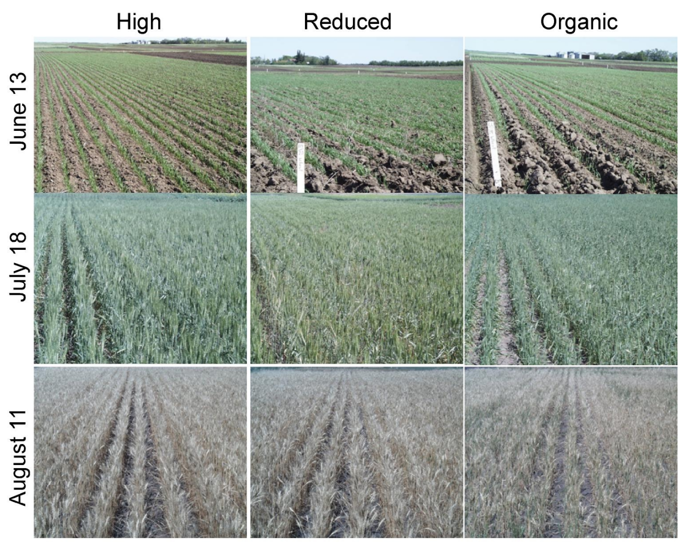


Figure 5. Wheat under three input levels at the three growing stages.

The large LAI values suggest the optimal time to monitor growth and vigor of the crop using remote sensing in Saskatchewan is from June 20 to July 20, when wheat is in late stem elongation stage to heading (florescence) phase. During this period, measurements could be used to predict wheat yields. In early August, the monitoring is unreliable because the color and moisture content cause variable results. Therefore, the further analyses focused on data from July.

*Correlation analysis between wheat LAI and primary spectrum*

Figure 6 shows that the correlations between LAI and reflectance were negative when the wavelengths are less than 722 nm with correlation coefficients being maximum and formed a valley at 684 nm. The correlations were positive when wavelengths are larger than 723 nm with a maximum at 764 nm, and the correlation coefficients decreased slowly after 770 nm. The relationships were significant for the visible region (400-700 nm except for 520-580 nm) and infrared region (740-924). The maximum coefficients at 684 nm and 764 nm were –0.657 and 0.620, respectively. Therefore, it can be considered that the optimum hyperspectral regions should be inside 600-700 nm and 740-900 nm, in which the sets of spectrum reflectance and vegetative index can be used to monitor wheat LAI.

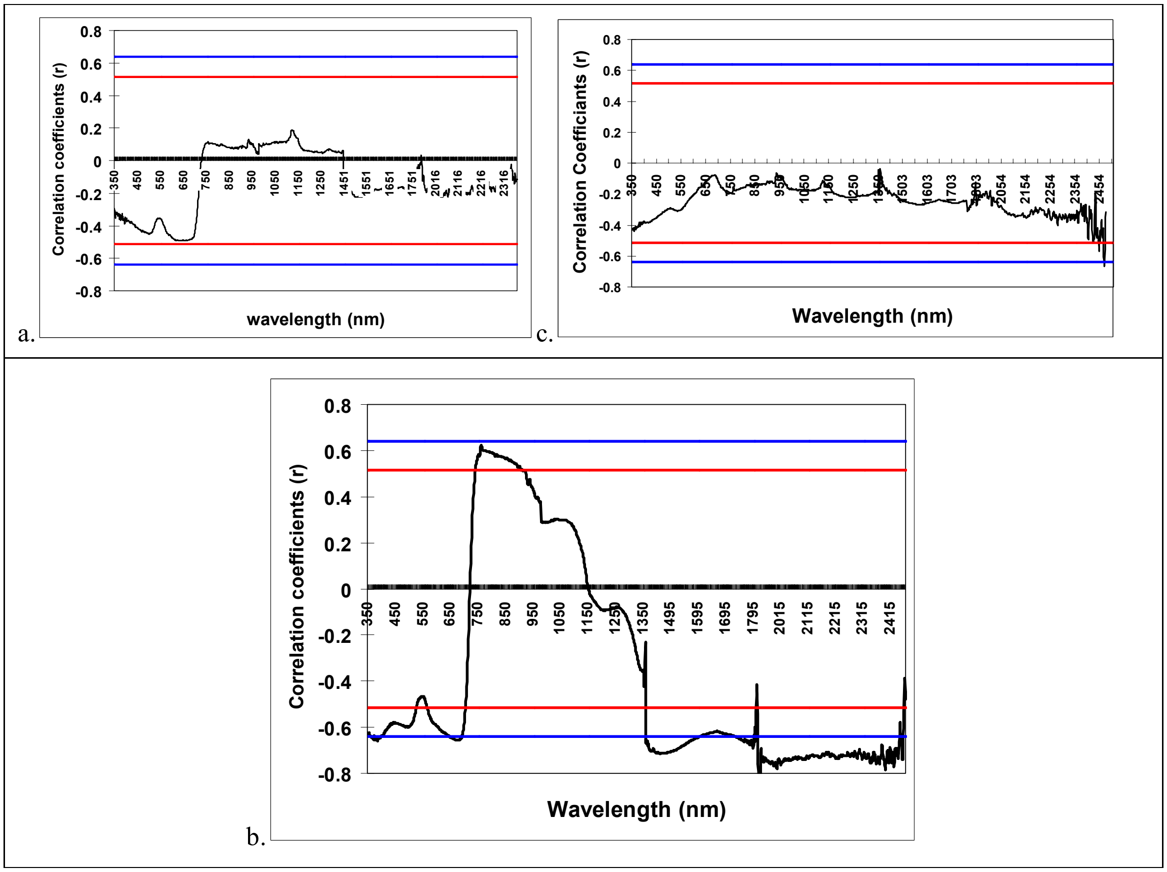


Figure 6. Correlation coefficients between LAI and hyperspectral single band over the growing seasons, June 13 (a), July 18 (b) and August 11 (c). The red lines are critical significant r values at p=0.05 and blue lines are critical r values at p=0.01.

*Correlation analysis between wheat LAI and the first derivative*

In the region of 550-900 nm, the relations between LAI and the first derivative were negative inside 552-681 and 830-900 nm, while were positive in the region of 706-755nm. All the correlation coefficients are significant; the maximum coefficients are –0.789 and 0.769, at 631 and 742nm, respectively (Figure 7). The wavelength of 742 nm is the most variable band within red edge region. The analysis revealed that regions of 550-680 nm and 710-760 nm were optimal regions to measure wheat LAI.

***Estimating models of monitoring wheat LAI using hyperspectral remote sensing data***

*Selection of variables and vegetative indices*

Based on analyses above, the spectrum reflectance of red valley and near infrared peak inside regions of 600-700nm and 740-900nm and their located band positions were selected as variables, as were peak and valley of first derivative spectrum within regions of 550-680nm and 710-760nm and their positions in regions (Table 1). Peak of red edge (680-780nm), red edge position and red edge area are usually used to monitor chlorophyll, physiological activity and biomass of crops (Boochs et al. 1990, Filella et al. 1994) and were selected as variables. Studies of applying conventional remote sensing data to agriculture have shown that vegetative indices are important variables. Therefore, in this study, the ratio vegetative index, normalized vegetative index (NDVI), simple vegetative index and logarithm vegetative index were chosen. A total of 15 spectral variables were selected to relate to wheat growth and vigor (Table 1). The analysis was carried out to determine whether these factors can be used to predict wheat LAI. Two statistical methods were used in this study. First, correlation analysis was applied to verify if the correlation coefficients were significant. Second, a stepwise multiple regression method was used to select variables for the prediction equation.

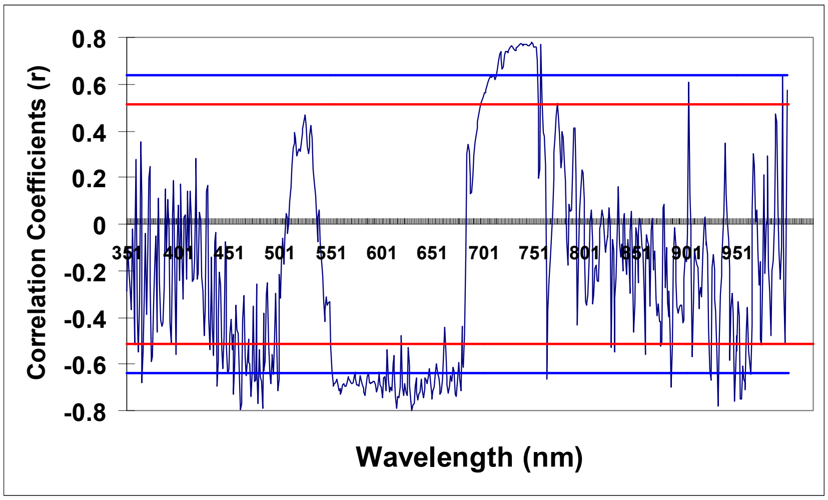


Figure 7. Correlation coefficients between LAI and spectral first derivative. The red lines are critical significant r values at p=0.05 and blue lines are critical r values at p=0.01.

Table 1 shows that the correlation coefficients between the hyperspectral variables and wheat LAI are highly significant except for X3, X4 and X8. The coefficient of X12 (ratio vegetative index) was the highest (r= -0.8249), and the second highest was NDVI (r=0.824). The data suggest that the changes in these variables are related to wheat LAI. Further, the stepwise regression analysis indicated that only one factor, the ratio vegetative index, was needed to account for the majority of the variation of wheat LAI. The remaining variables were highly correlated with the ratio vegetation index and are not required to explain the variation in wheat LAI.

*Model development*

The ratio vegetative index was correlated negatively to wheat LAI, illustrating that the smaller the index, the larger the LAI. Linear, logarithm and exponential models were tested and the exponential model was found to give the best fit ($R^2$= –0.732, p=<0.001 (Table 2).

Table 1. Correlation coefficients between the hyperspectral variables and wheat LAI.

| Variables | Correlation coefficient(r) | description |
|---|---|---|
| X1 | -0.7845** | the minimum spectral reflectance within red region of 600-700nm |
| X2 | 0.7306** | corresponding wavelength of red valley |
| X3 | 0.5085* | the maximum spectral reflectance within near infrared region of 740-900nm |
| X4 | -0.5520* | corresponding wavelength of near infrared peak |
| X5 | 0.7449** | The minimum$1^{st}$ derivative spectrum within regions of 550-680nm and 710-760nm |
| X6 | 0.7496** | corresponding wavelength of the minimum$1^{st}$ derivative spectrum |
| X7 | -0.6525** | The maximum$1^{st}$ derivative spectrum within region of 710-760nm |
| X8 | -0.1182 | corresponding wavelength of the maximum$1^{st}$ derivative spectrum |
| X9 | 0.7449** | The maximum$1^{st}$ derivative spectrum within red edge region of 680-780nm |
| X10 | 0.7775** | Red edge position, that is, corresponding wavelength of the maximum red edge |
| X11 | 0.7252** | Red edge area |
| X12 | -0.8249** | Rr/Ri, ratio vegetative index |
| X13 | 0.8240** | (Ri-Rr)/(Ri+Rr)，normalized vegetative index(NDVI) |
| X14 | 0.6763** | Ri-Rr simple vegetative index |
| X15 | 0.8151** | Log(Ri/Rr) logarithm vegetative index |

Note: r with * and ** denote those that have passed significance tests at 0.05 and 0.01, respectively (the same below).

*Model Validation*

Table 2 indicates that preferable variables are X12 (ratio vegetative index) and X13 (NDVI). The exponential model performed better when wheat LAI was estimated by hyperspectral remote sensing data with correlation coefficients being 0.732 and 0.727, F variance value being 35.53 and 34.62 for the two spectral variables. When the equations of $y > 2.3575e^{\cdot 4.8957X_{12}}$ and $y > 0.082e^{3.5448X_{13}}$ were fitted to calculate LAI, differences between observed LAI and simulated LAIs are 1.515%and 1.32%, which means the models are very good at monitoring wheat LAI (Figure 8).

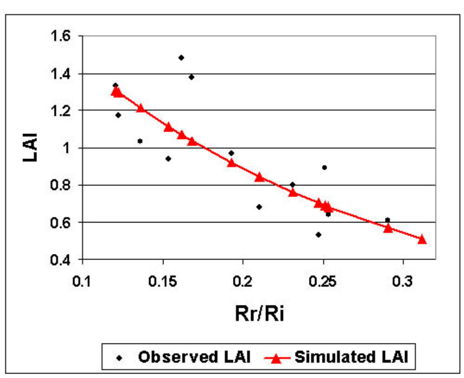


Figure 8. Model fitting test for using ratio vegetation index.

Table 2 Hyperspectral estimating models of monitoring wheat LAI

| Variables | Models | b0 | b1 | $R^2$ | F | *P* |
|---|---|---|---|---|---|---|
| X1 | LIN | 1.9422 | -20.711 | .615 | 20.72 | .001 |
| | LOG | -2.2591 | -1.0474 | .620 | 21.23 | .000 |
| | EXP | 2.8639 | -24.148 | .684 | 28.20 | .000 |
| X2 | LIN | -4.2661 | .0080 | .534 | 14.88 | .002 |
| | LOG | -32.067 | 5.0950 | .532 | 14.75 | .002 |
| | EXP | .0020 | .0093 | .596 | 19.14 | .001 |
| X5 | LIN | .4275 | -1949.9 | .426 | 9.64 | .008 |
| | EXP | .4958 | -2224.0 | .454 | 10.80 | .006 |
| X6 | LIN | .0330 | 262.350 | .555 | 16.20 | .001 |
| | LOG | 5.8203 | .8561 | .554 | 16.12 | .001 |
| | EXP | .3194 | 296.111 | .579 | 17.89 | .001 |
| X7 | LIN | -37.790 | .0534 | .605 | 19.88 | .001 |
| | LOG | -253.42 | 38.6148 | .604 | 19.86 | .001 |
| | EXP | 9.2E-21 | .0634 | .699 | 30.22 | .000 |
| X9 | LIN | .0330 | 262.350 | .555 | 16.20 | .001 |
| | LOG | 5.8203 | .8561 | .554 | 16.12 | .001 |
| | EXP | .3194 | 296.111 | .579 | 17.89 | .001 |
| X10 | LIN | -36.235 | .0512 | .562 | 16.67 | .001 |
| | LOG | -243.22 | 37.0653 | .562 | 16.67 | .001 |
| | EXP | 3.3E-20 | .0617 | .667 | 26.03 | .000 |
| X11 | LIN | -.0683 | 5.8562 | .526 | 14.42 | .002 |
| | LOG | 2.6585 | .9630 | .526 | 14.41 | .002 |
| | EXP | .2844 | 6.6212 | .551 | 15.94 | .002 |
| X12 | LIN | 1.7904 | -4.2719 | .680 | 27.67 | .000 |
| | LOG | -.4385 | -.8307 | .664 | 25.73 | .000 |
| | EXP | 2.3575 | -4.8957 | .732 | 35.53 | .000 |
| X13 | LIN | -1.1436 | 3.1009 | .679 | 27.50 | .000 |
| | LOG | 1.7649 | 2.0367 | .680 | 27.60 | .000 |
| | EXP | .0822 | 3.5448 | .727 | 34.62 | .000 |
| X14 | LIN | -.2107 | 5.6480 | .457 | 10.95 | .006 |
| | LOG | 2.7006 | 1.0953 | .448 | 10.56 | .006 |
| | EXP | .2449 | 6.3275 | .470 | 11.53 | .005 |
| X15 | LIN | -.4385 | 1.9127 | .664 | 25.73 | .000 |
| | LOG | 1.4087 | 1.3598 | .676 | 27.17 | .000 |
| | EXP | .1851 | 2.1779 | .706 | 31.17 | .000 |

## Conclusions

Results showed that hyperspectral remote sensing can be used to indicate different crop conditions. The spectral and LAI differences among input levels were significant at early to mid growing seasons. Late to mid July is the best season and the red over near infrared spectral ratio as well as the normalized difference vegetation index based on these two bands are the best vegetation indices to use remotely sensed data for wheat vigor monitoring. Based on the fact that the conclusions were based on field data in one growing season, the results may be differ in years with different growing conditions (i.e. the season may affect the timing of measurements). Further study will be conducted to include some meteorological data to "characterize" the growing season and a second growing season field campaign will be conducted.

**Acknowledgements**

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